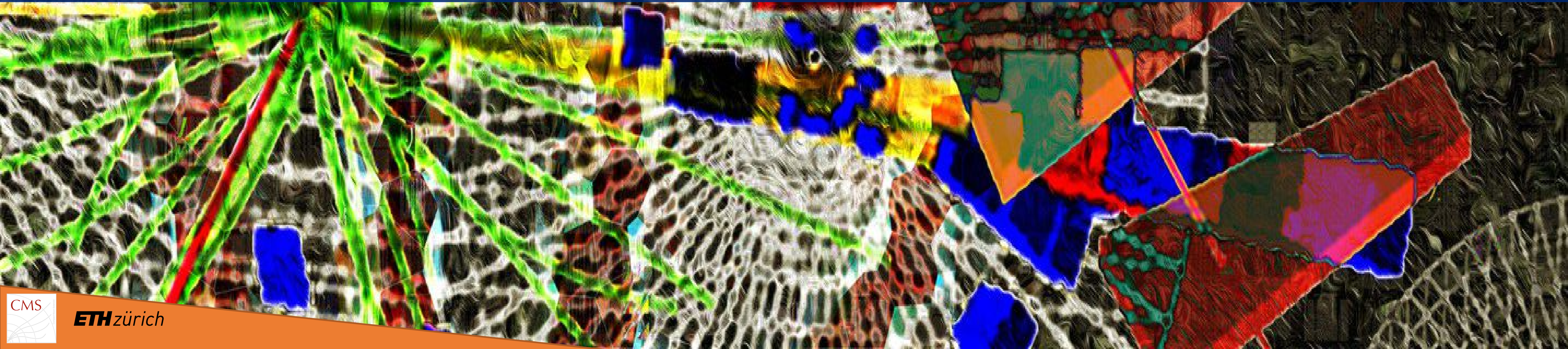
Electromagnetic Shower Corrections in CMS

X. Chang, G. Dissertori, M. Donegá, M. Galli, P. Musella, S. Pigazzini, T. Reitenspiess

22 March 2023



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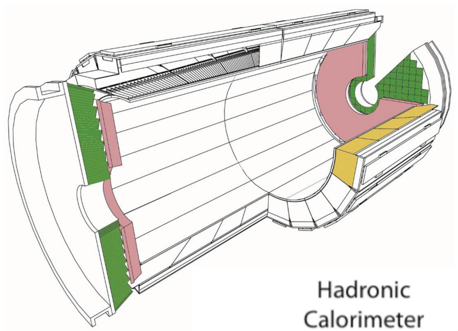
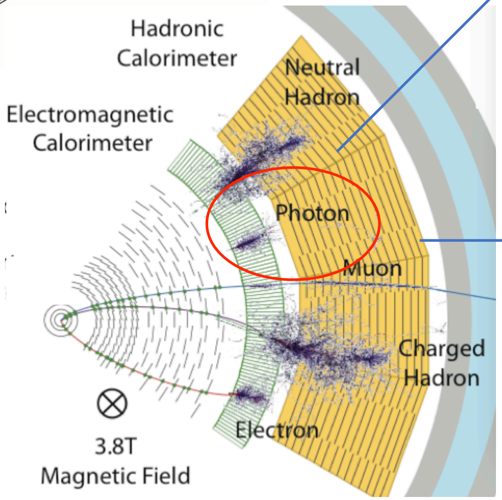
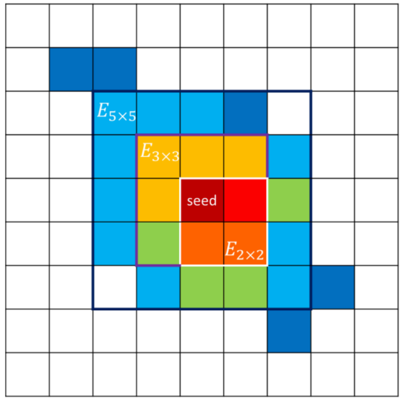
Simulation of Electromagnetic Variables

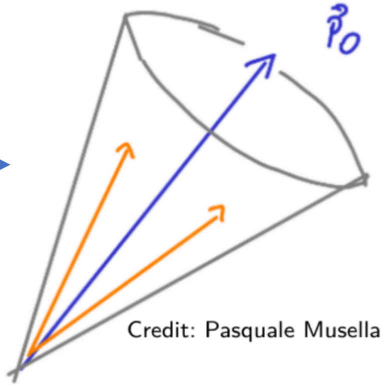
- Monte Carlo (MC) used in all the analyses with CMS data
- When it comes to analyses that use **photons** (e.g. $H \rightarrow \gamma\gamma$), the description of the **electromagnetic shower** in the ECAL is crucial:







Shower shape variables: describe the shape of the EM shower cluster in the calorimeter



Isolation variables: characterize the activity around the object of interest

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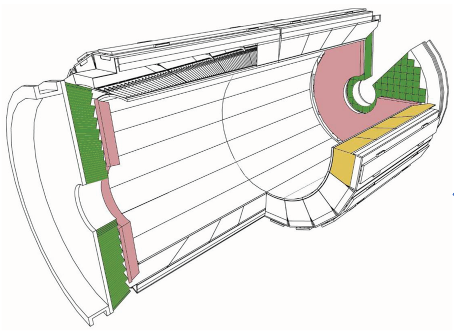
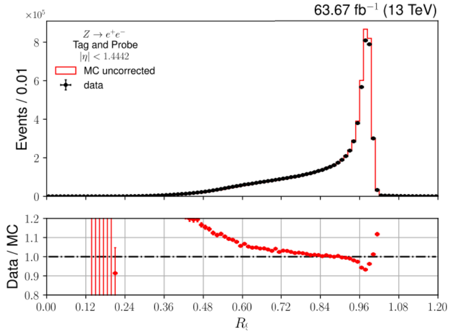
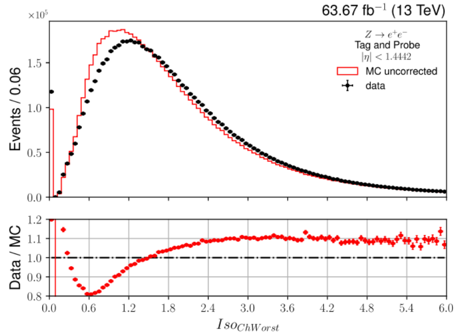


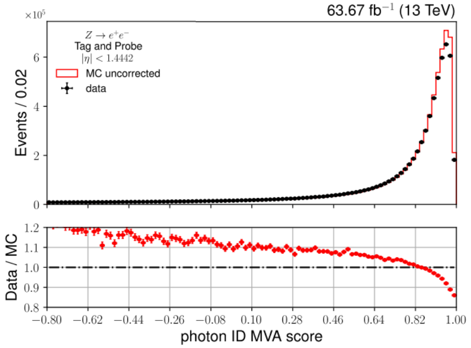
Detector aging makes it difficult to correctly simulate the shower development





Data - MC mismatch in shower shapes and isolation variables

ID MVA



Disagreement propagated to **photon identification**…

… which ultimately results in **higher systematic uncertainties**

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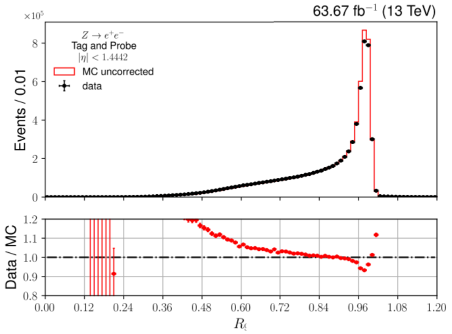

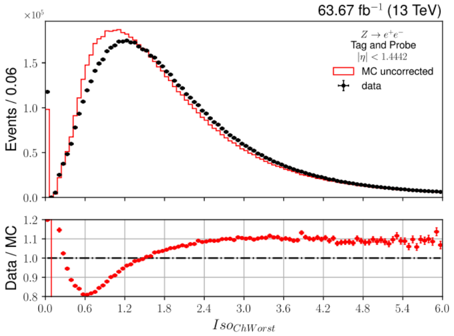

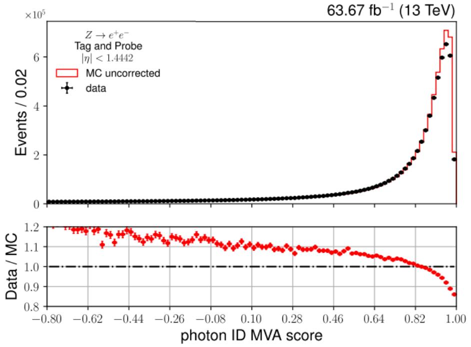

Developed a procedure called Chained Quantile Regression (**CQR**) to match MC with data (and hence decrease systematic uncertainties)

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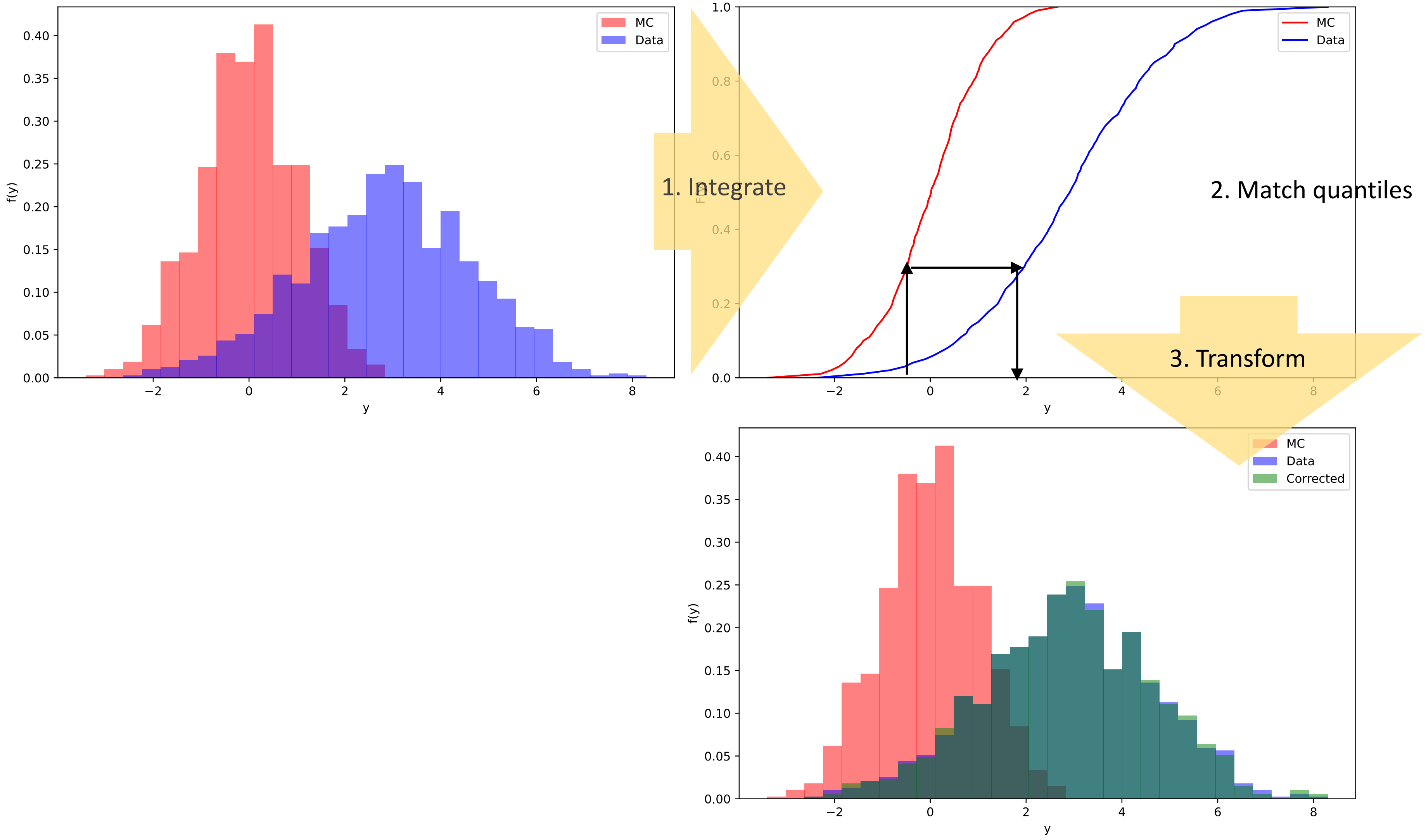
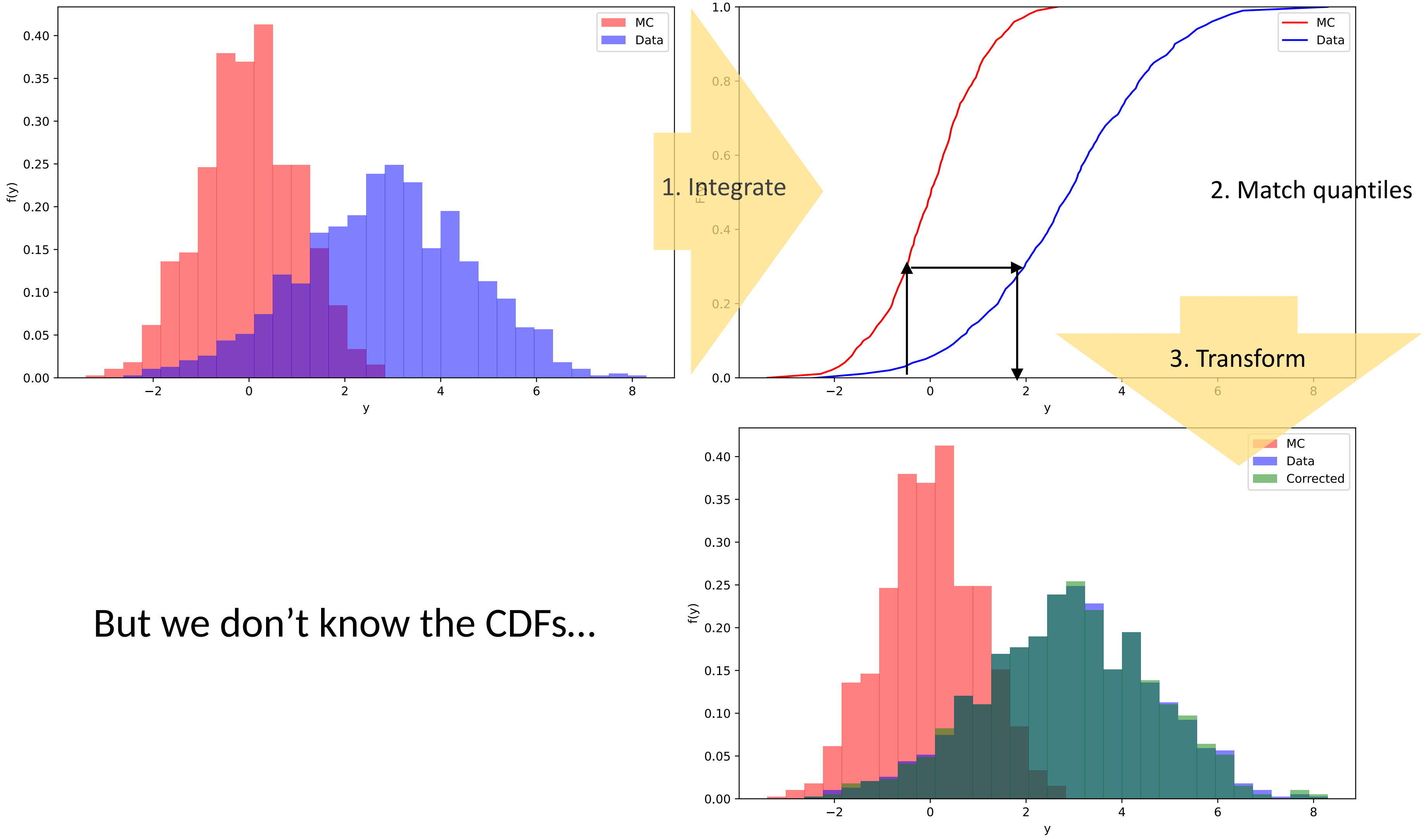
Quantile Morphing



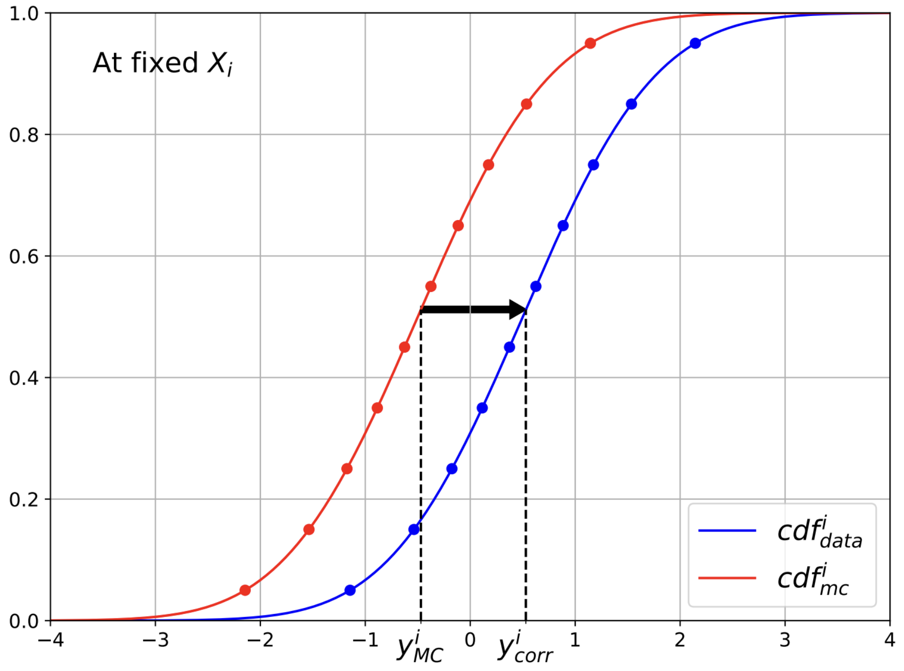
Quantile Morphing



But we don’t know the CDFs…

Quantile Regression

- Cumulative Distribution Function (**CDF**) of both data and MC depend on kinematic quantities $X = [p_t, \eta, \phi, \rho]$ - which describe the physics of the shower
- **Train regressors** to predict the conditional shape of CDFs using **21 quantiles**
- To correct a certain variable y_i^{MC}:
  - Find two quantiles around y_i^{MC} for data and MC
  - Use linear interpolation between the two points to obtain $cdf^{data}(y_i\,|\,X_i)$ and $cdf^{MC}(y_i\,|\,X_i)$
  - Compute $y_i^{MC,corr}$ by solving $y_i^{MC,corr} = cdf^{-1}_{data}(cdf^{MC}(y_i^{MC}\,|\,X_i))$



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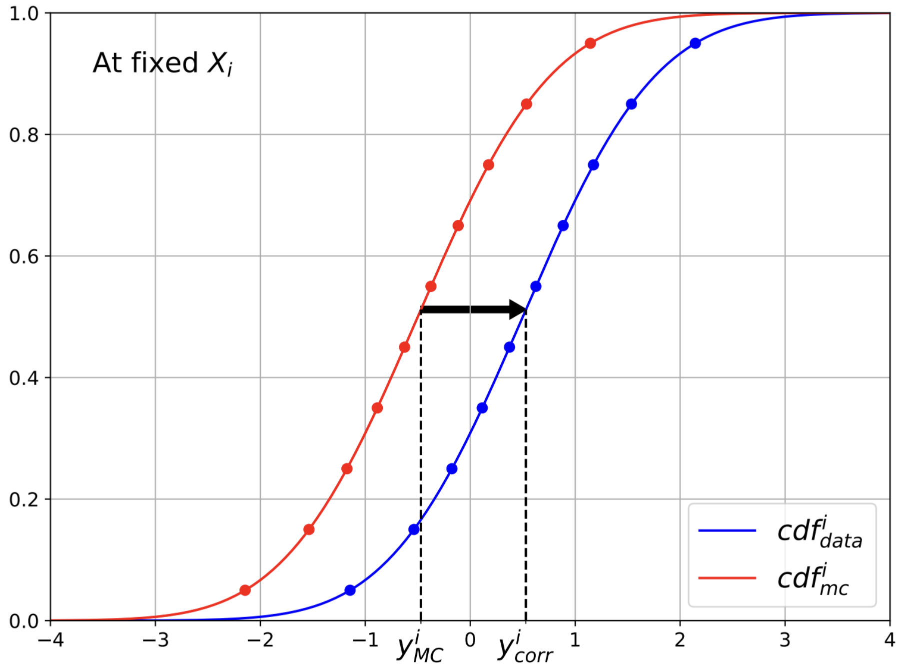

But this is not enough because the variables are correlated...

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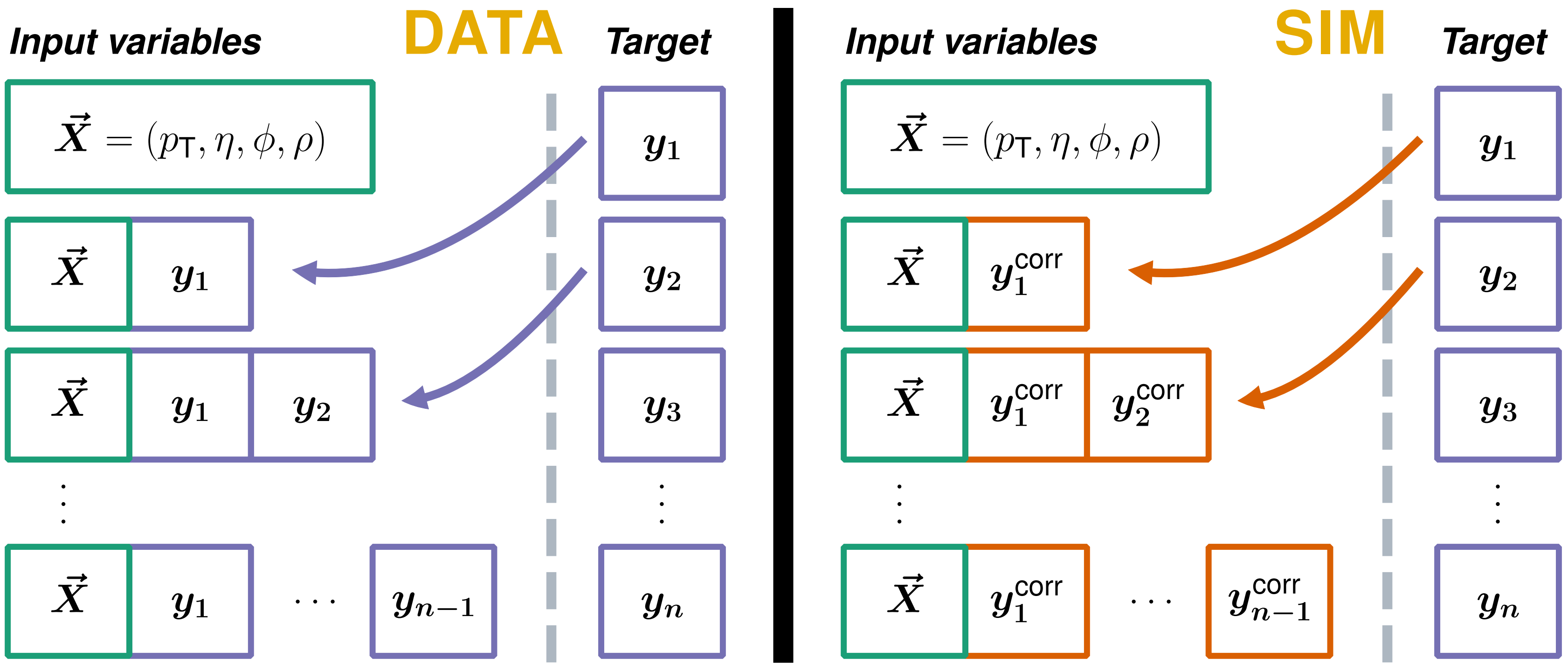
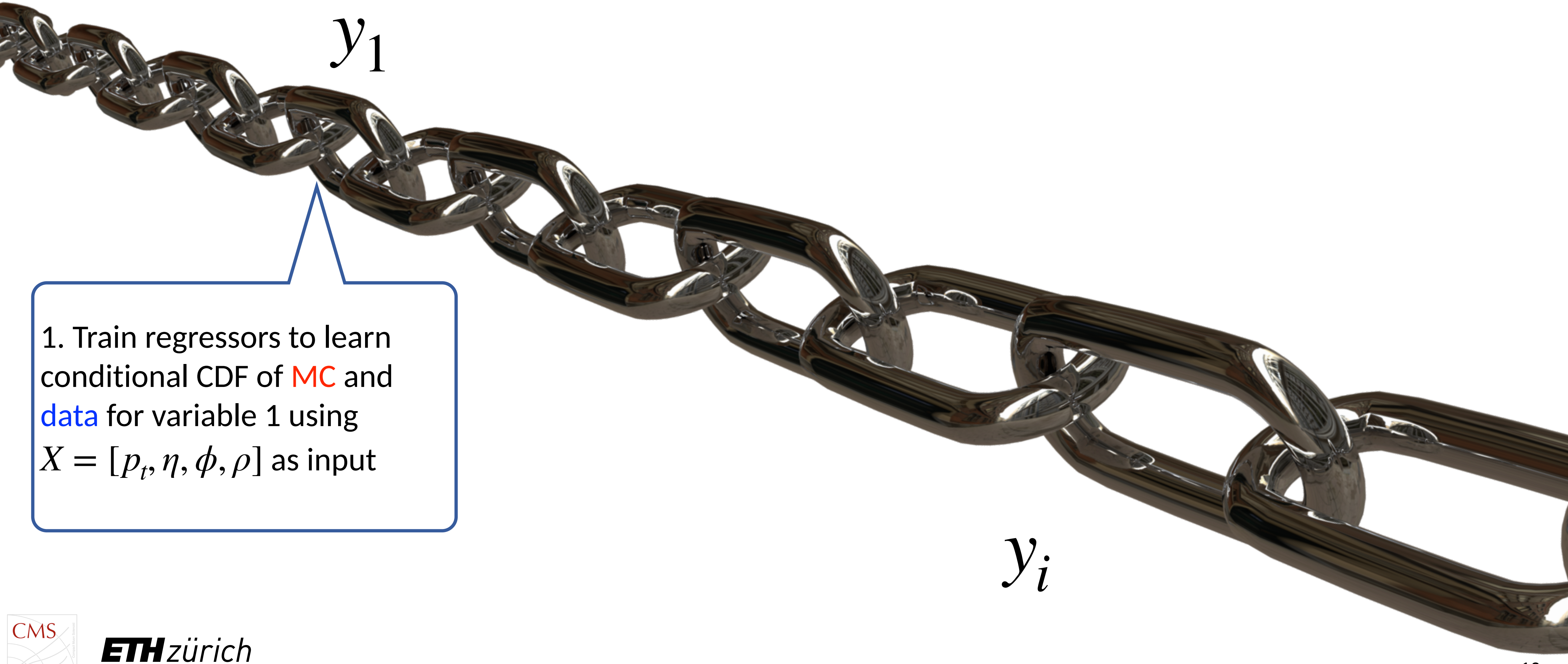
Chained Quantile Regression

- In order to **catch correlations** between the variables we are correcting we need to chain them:
  - Data: for target variable y_i input variables are $X = [p_t, \eta, \phi, \rho, y_1, \ldots, y_{i-1}]$
  - MC: for target variable y_i input variables are $X = [p_t, \eta, \phi, \rho, y_1^{corr}, \ldots, y_{i-1}^{corr}]$

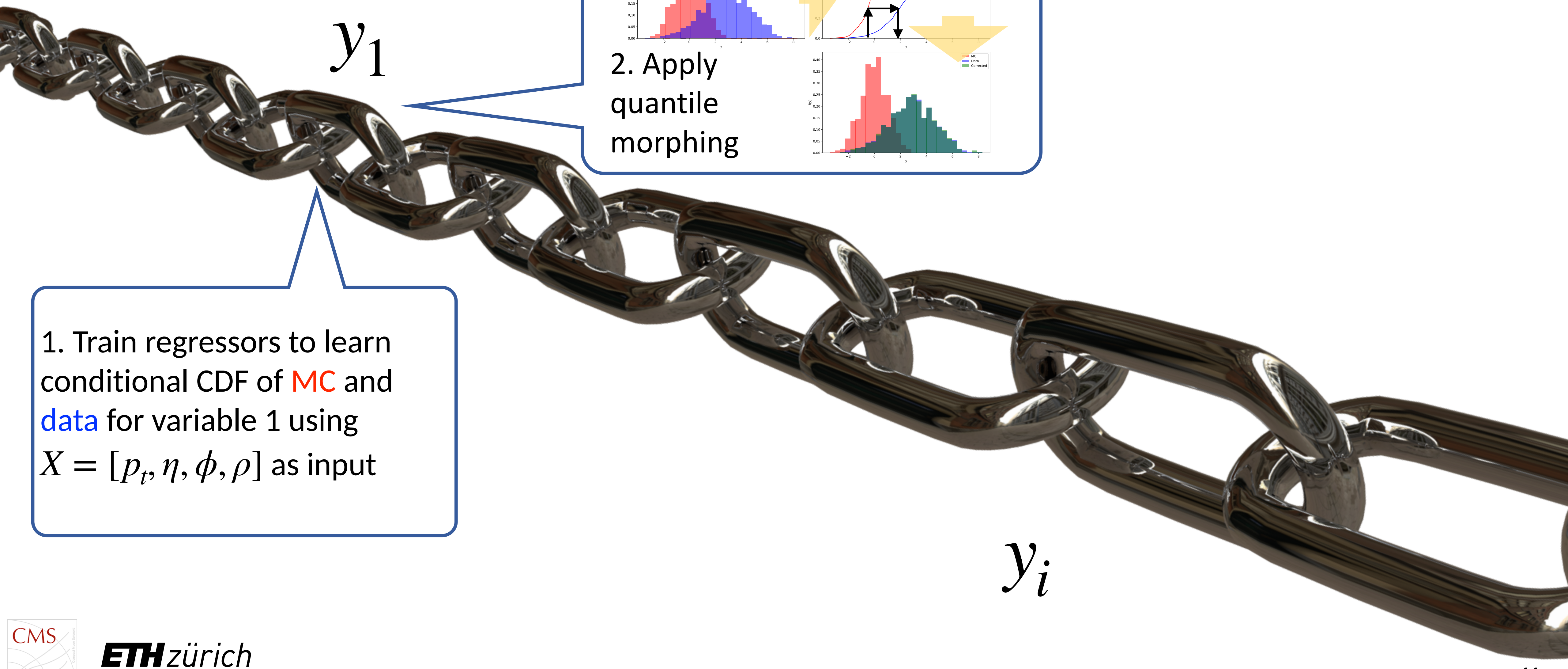


Chained Quantile Regression



1. Train regressors to learn conditional CDF of MC and data for variable 1 using $X = [p_t, \eta, \phi, \rho]$ as input

Chained Quantile Regression



y_1

2. Apply quantile morphing

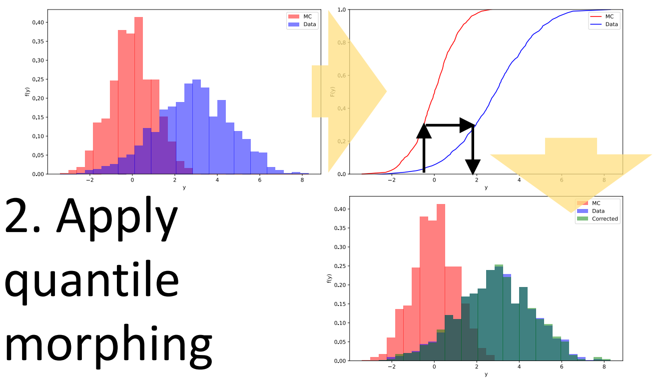
1. Train regressors to learn conditional CDF of MC and data for variable 1 using $X = [p_t, \eta, \phi, \rho]$ as input

y_i

Chained Quantile Regression

y_1

2. Apply quantile morphing



3. Repeat the procedure for variable i using

$X = [p_t, \eta, \phi, \rho, y_1, \ldots, y_{i-1}]$

(data)

$X = [p_t, \eta, \phi, \rho, y_1^{corr}, \ldots, y_{i-1}^{corr}]$

(MC) as input

1. Train regressors to learn conditional CDF of MC and data for variable 1 using $X = [p_t, \eta, \phi, \rho]$ as input

y_i

What are these regressors?

In its first implementation (still used in most $H \rightarrow \gamma\gamma$ analyses) **one BDT per quantile** was trained:

21 BDTs

x 9 variables

x 2 samples

x 2 detector parts

+ (...)

= many BDTs!

Computationally expensive and time consuming!

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21 BDTs
x 9 variables
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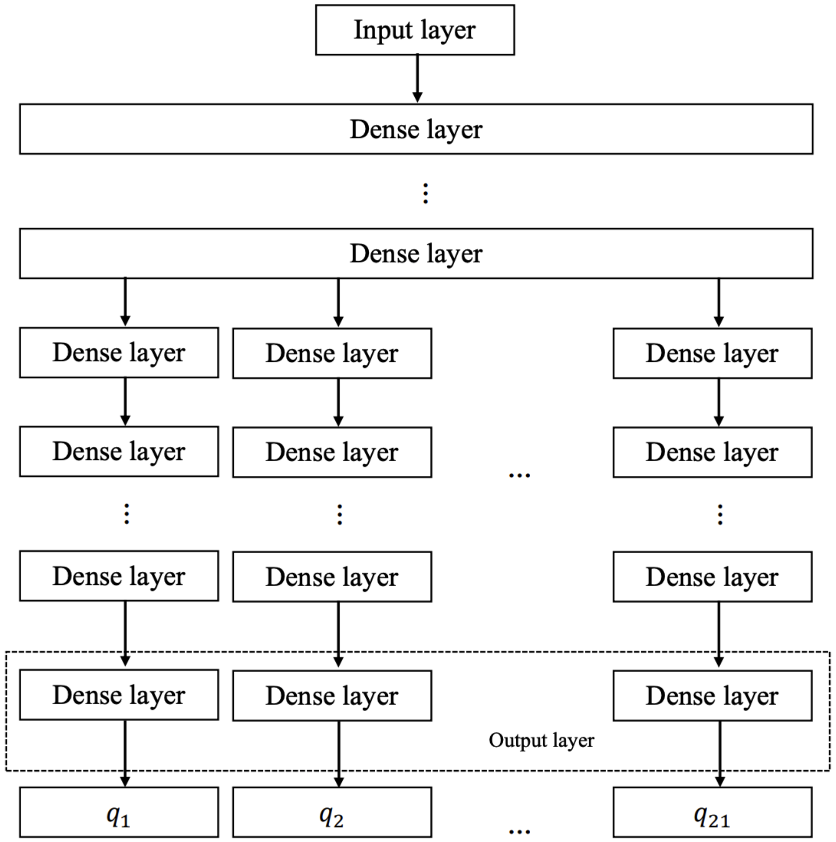
x 2 detector parts
+ (...)
= many BDTs!

Computationally expensive and time consuming!

In a second iteration of the work the 21 BDTs of each variable were replaced by a single **quantile regression neural network**:



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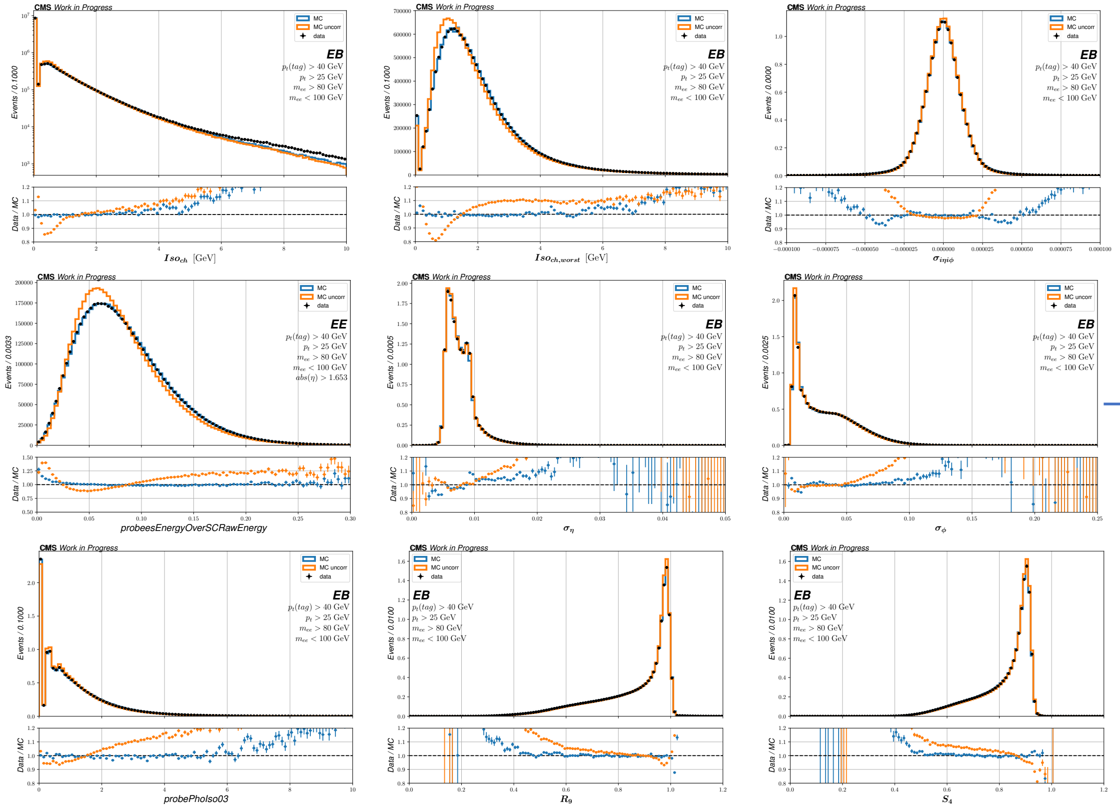
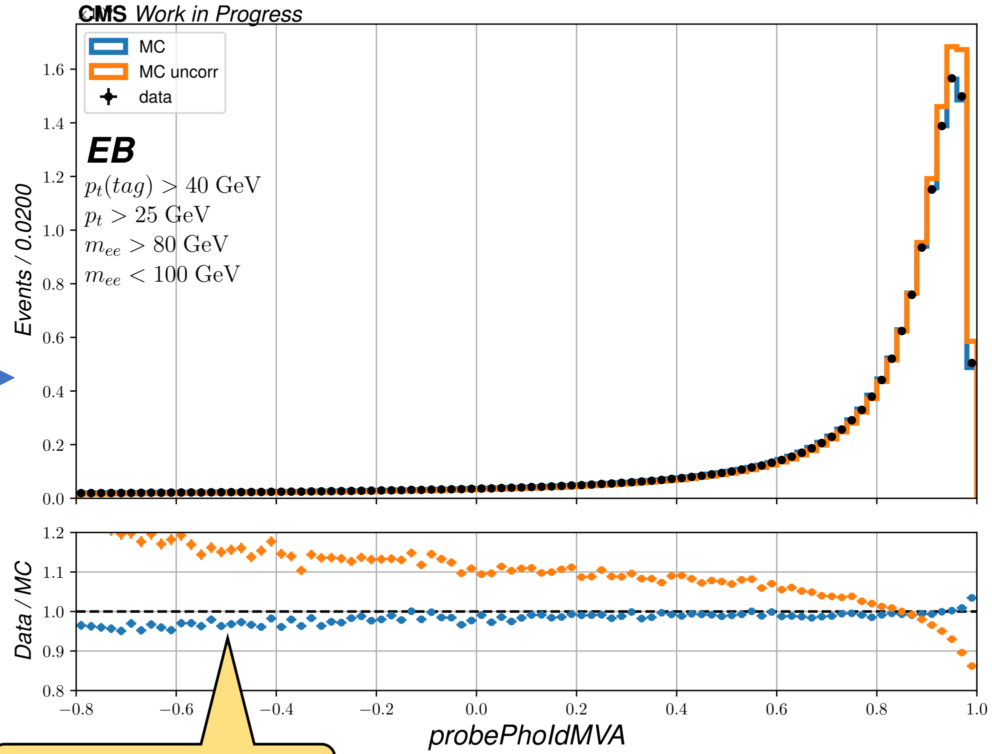
Corrected Distributions



ID MVA



Ratio closer to 1 = **better agreement**

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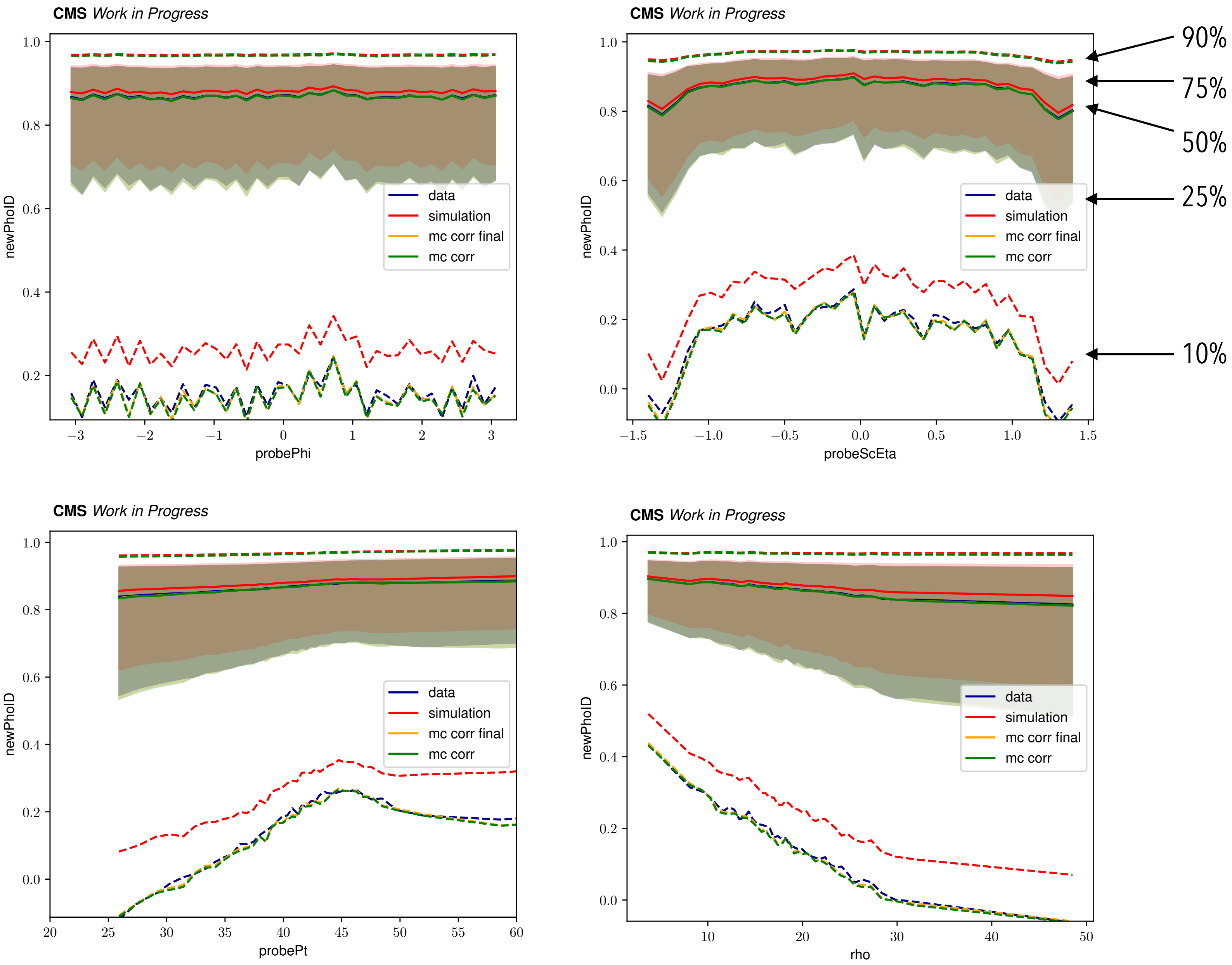
Profiles



CMS Work in Progress
newPhoID
probePhi
data
simulation
mc corr final
mc corr
CMS Work in Progress
newPhoID
probeScEta
data
simulation
mc corr final
mc corr
90%
75%
50%
25%
10%
CMS Work in Progress
newPhoID
probePt
data
simulation
mc corr final
mc corr
CMS Work in Progress
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rho
data
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mc corr

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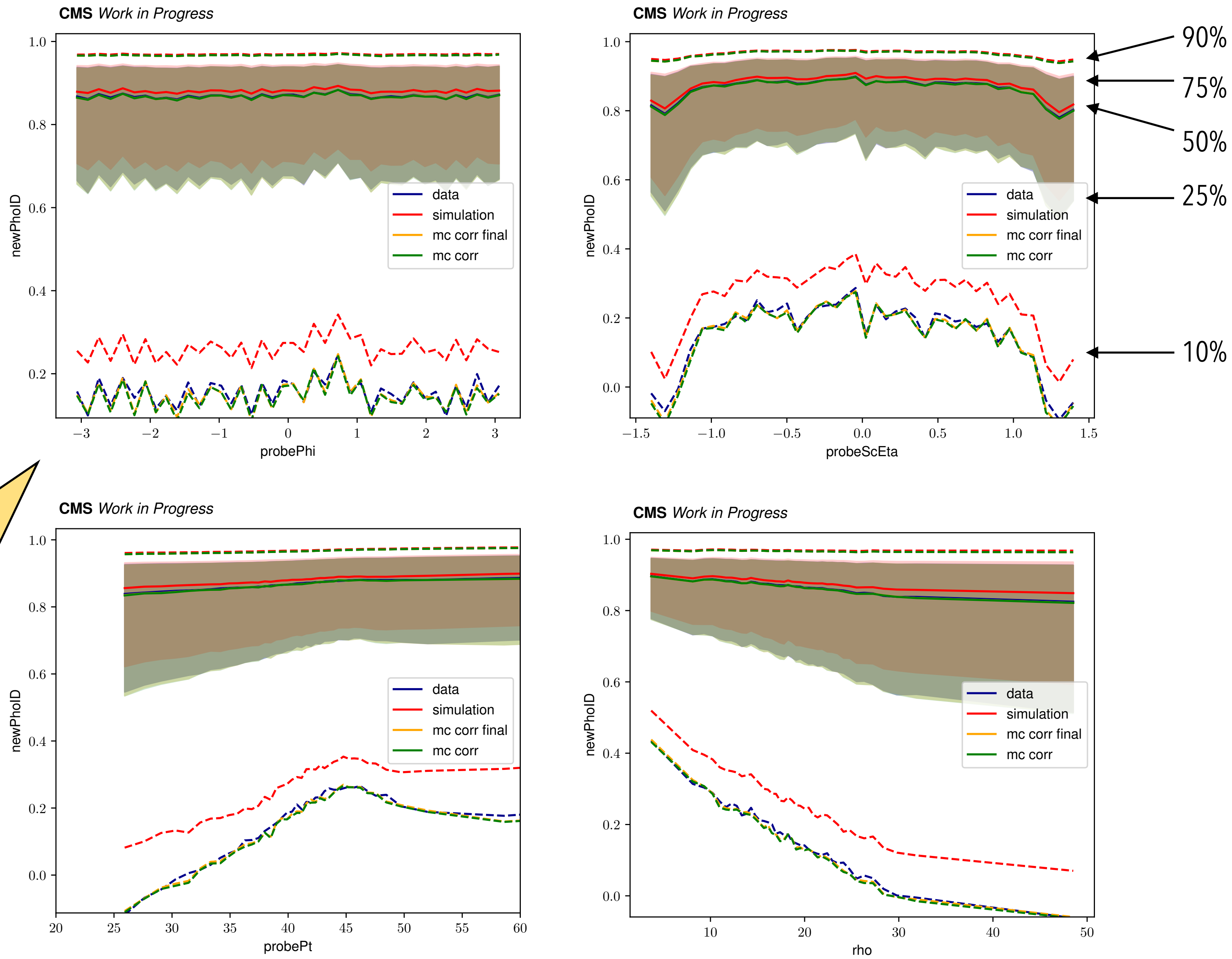
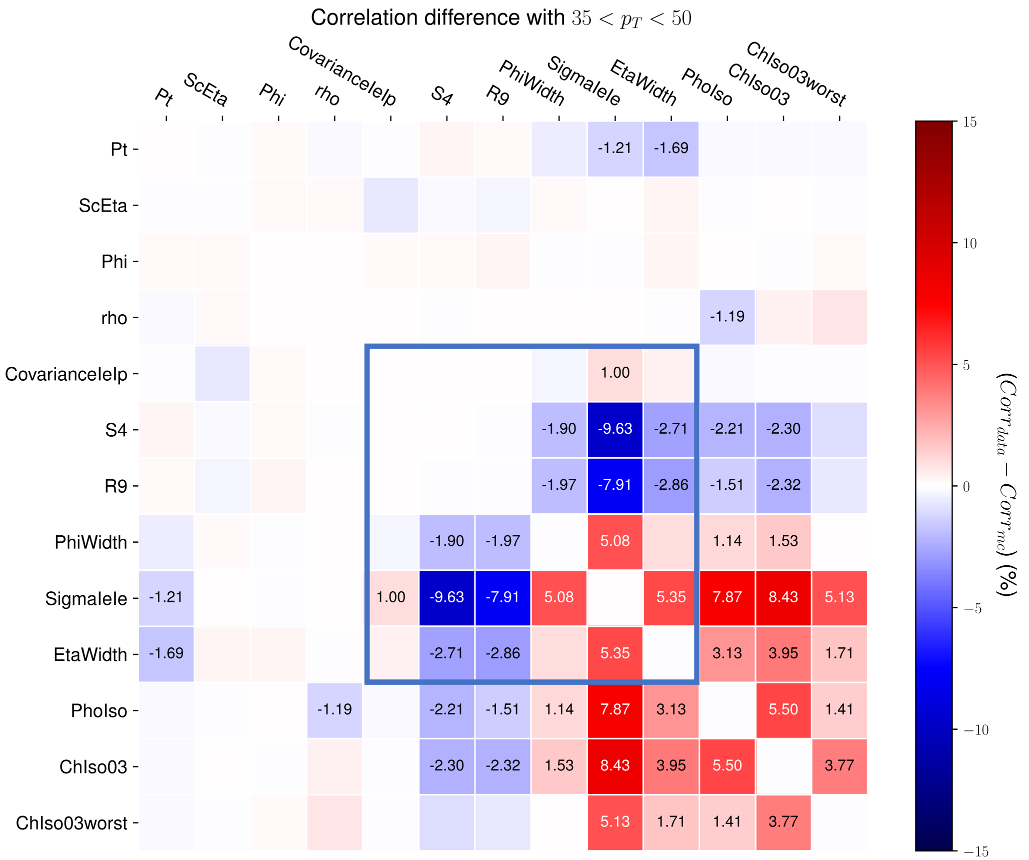
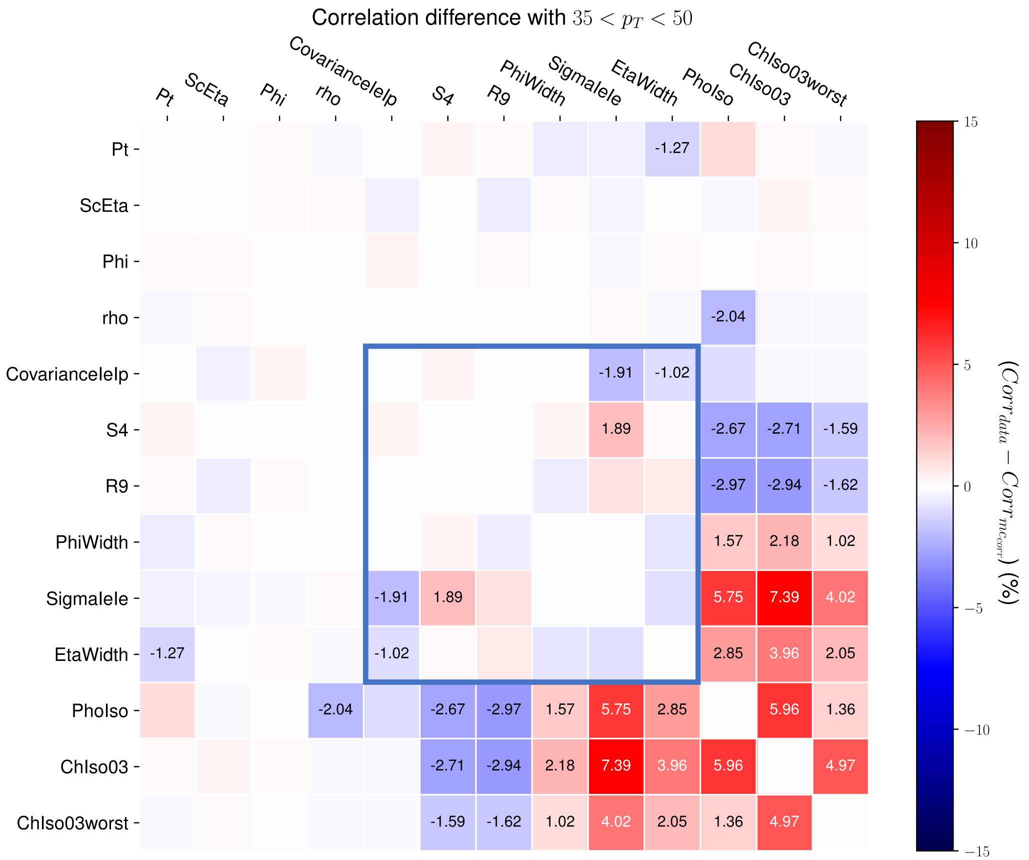


Closer agreement between data and MC corrected profiles

Correlations

Difference of correlation matrices between data and MC **before** (left) and **after** (right) corrections:





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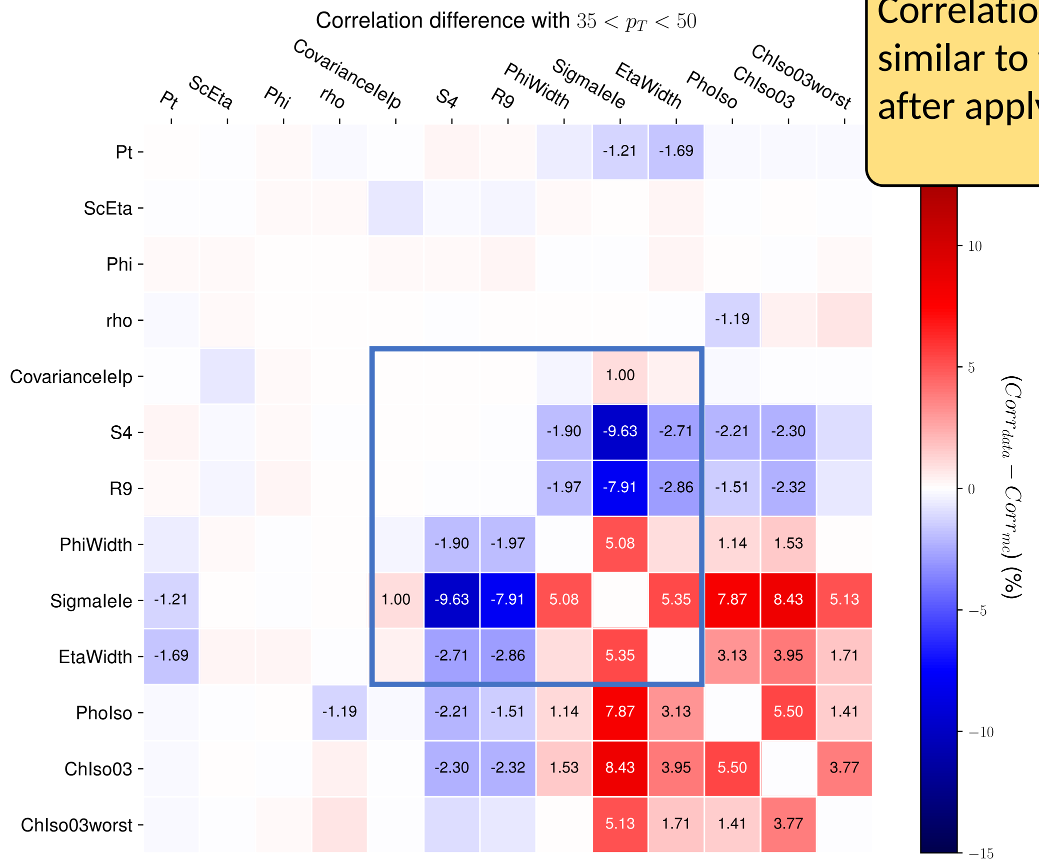
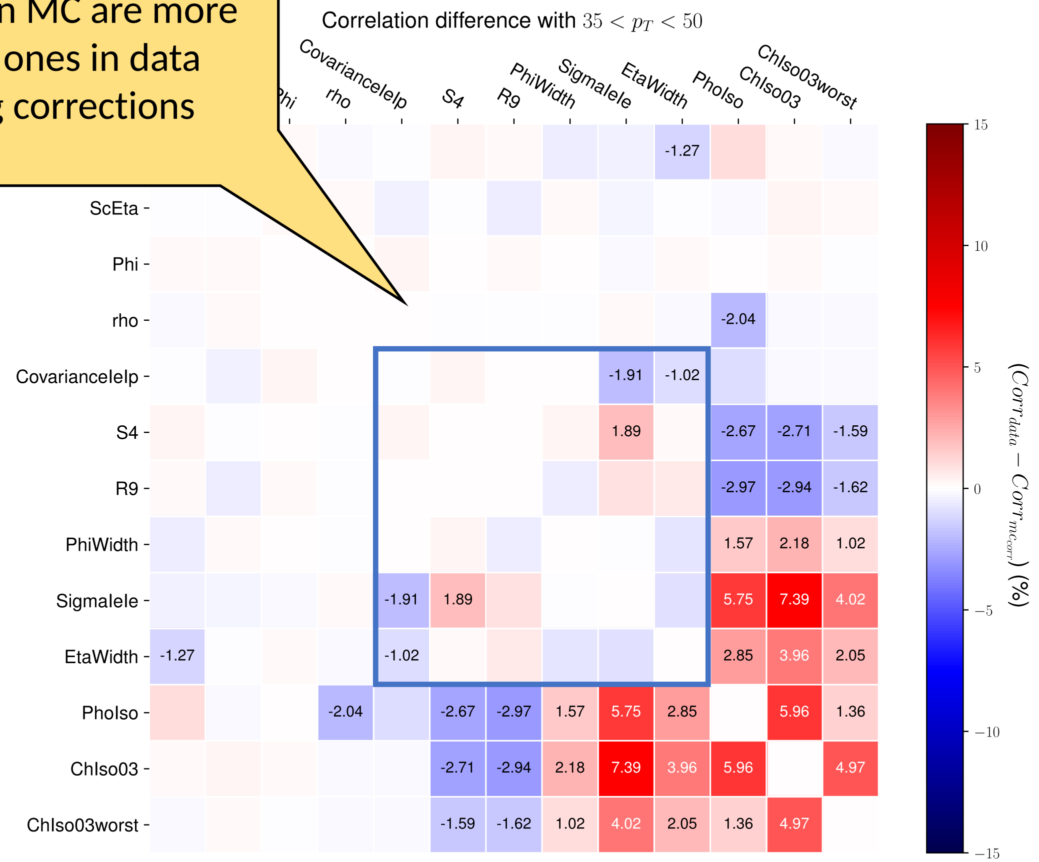
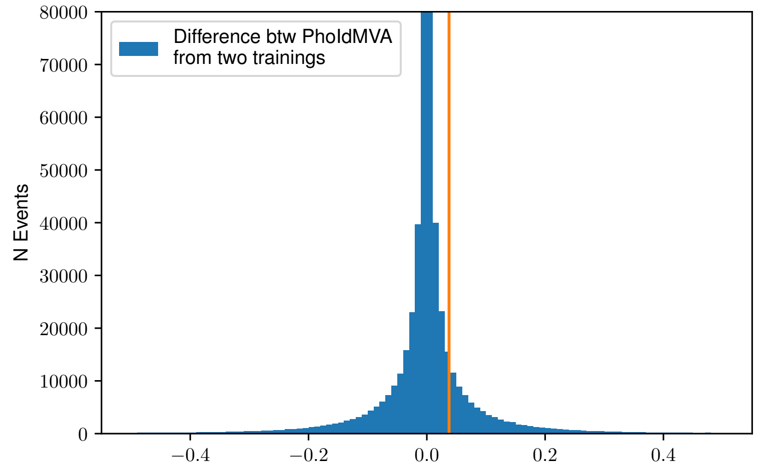


Correlations in MC are more similar to the ones in data after applying corrections

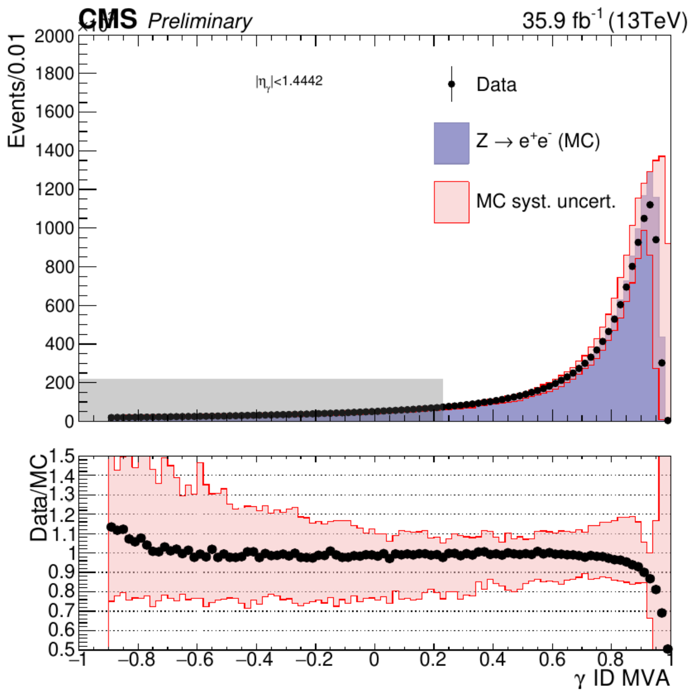


Systematic Uncertainties

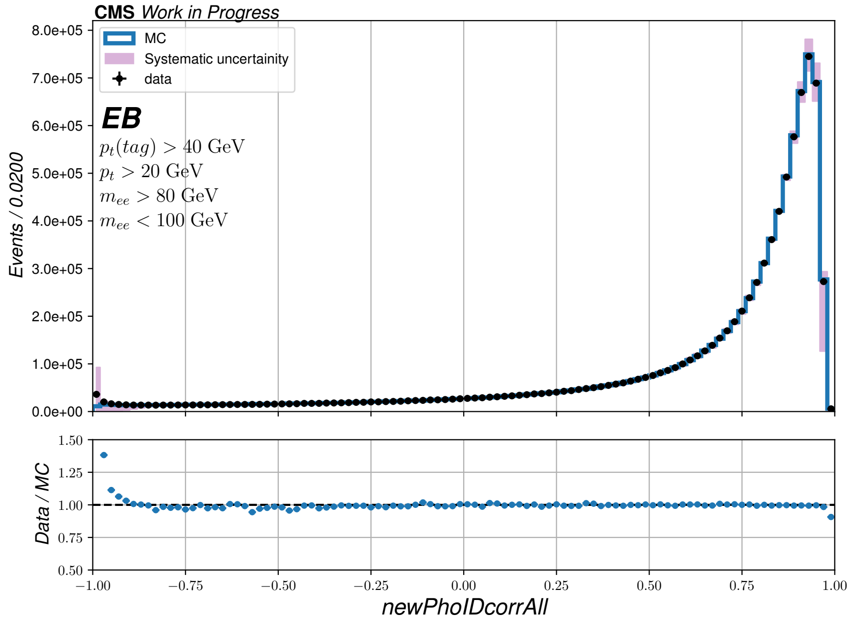
- Correction scheme accounts for all uncertainties and correlations → the only uncertainty comes from **finite size** of training sample
- Split the training sample in two and derive $\pm 1\sigma$ from the RMS of the $PhoID_1 - PhoID_2$ distribution



Run 1 Analysis (no corrections)



Run 2 Analysis



Future Prospects: Normalizing Flows

Also in its NN implementation, the CQR requires to train models and regressors one after the other to **take correlations into consideration**

Takes a long time and the corrected distributions need to be checked at every step

Normalizing flows allow to model high dimensional conditional distributions (see D. Valsecchi's talk)

Benefit: chain is removed, making the training simpler and faster

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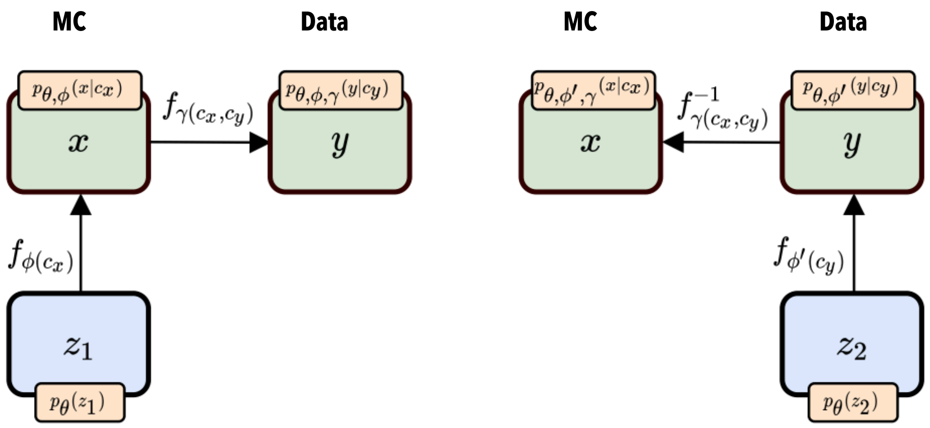

From Flow4Flow paper

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Benefit: chain is removed, making the training simpler and faster

As showed in arXiv:2211.02487 it is possible to train a system of three normalizing flows able to map two multidimensional conditional distributions into one another…
But does this procedure reach the level of precision that we require?

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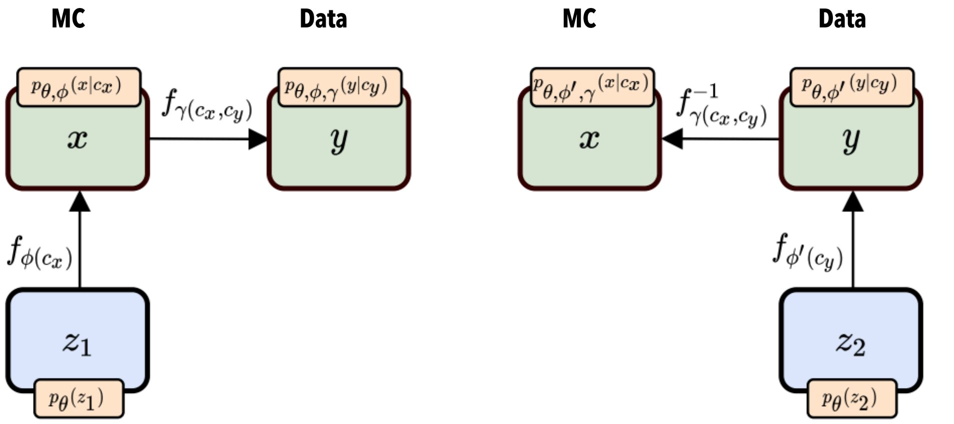
Future Prospects: Normalizing Flows

If you find this idea interesting and you want to work on it, we are offering this as a semester project - **Contact us!**



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Thank you for your attention!

Backup

Correction Approach

- Developed procedure called **Chained Quantile Regression** (**CQR**) to match data with MC (and hence decrease systematic uncertainties)
- Corrections are derived using Tag & Probe method on $Z \rightarrow e^+e^-$ events, with the reconstruction of the probe leg as a photon
- PhotonID score is re-evaluated with corrected variables